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Prediction of temporal and spatial variations of the NDDI drought index in the Khorramabad watershed using remote sensing

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Abstract

Abstract

Remote sensing-based indices are effective tools for monitoring drought and wet conditions. In this study, the Normalized Difference Drought Index (NDDI), derived from NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) data obtained from Sentinel-2 satellite imagery, was employed to assess drought conditions. Time series of these indices were generated using coding in the Google Earth Engine (GEE) platform, and the NDDI was subsequently calculated in Excel. Additionally, future predictions of the NDDI were conducted using time series modeling techniques. The results indicate that the NDDI is a reliable indicator for representing droughts caused by water scarcity and reduced vegetation cover. Analysis of NDDI values from 2016 to 2023 in the Khorramabad watershed revealed a range between -3.20 and -11.21, suggesting that the region generally experienced very low drought intensity during this period. Furthermore, drought prediction results based on NDDI, using time series modeling, identified the MA2 model as the most accurate, with a high coefficient of determination ($R^2 = 0.92$) and an Akaike Information Criterion (AIC) value of less than 50. The findings indicate that the decline in NDDI during the spring (-5.3) and winter (-5.4) of 2024 reflects improvements in relative vegetation cover, precipitation levels, and water reserves. However, an increase in this index during the summer and autumn (approximately -3) of 2024 suggests worsening drought conditions and reduced rainfall. This trend is projected to persist across different seasons in 2025 and 2026. In conclusion, the NDDI is recommended as a valuable tool for analyzing vegetation cover status and water fluctuations, enabling optimal watershed management strategies.

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Introduction

Drought is one of the most complex and destructive natural phenomena, profoundly affecting all living organisms. It is defined as a deficiency in water resources compared to normal conditions, with far-reaching impacts on the environment, economy, and human societies. Drought is particularly detrimental to the agricultural sector, as reduced water availability leads to decreased crop production and threatens food security. This phenomenon also triggers significant social and economic consequences, including forced migration, increased water management costs, and social tensions (Mishra et al., 2022; Zeng et al., 2022; West et al., 2019; Lesk et al., 2016). In recent decades, numerous methods have been developed to study and assess drought, utilizing factors such as precipitation, soil moisture, temperature, vegetation indices, and other climatic variables. These methods aim to enhance the monitoring of drought conditions and evaluate their intensity and spatial extent. Commonly used indices include the Standardized Precipitation Index (SPI), soil moisture index, Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), and evapotranspiration index. These indices provide comprehensive insights into climatic conditions and the impacts of drought on natural resources, agriculture, and ecosystems, thereby supporting decision-making processes and mitigating the adverse effects of drought (Dalezios et al., 2019). Advancements in remote sensing technology have further enabled researchers to utilize various types of remote sensing data, including multispectral, thermal infrared, and microwave data, for large-scale drought monitoring. Remote sensing offers a comprehensive view of the Earth and a spatial framework for assessing drought impacts. It serves as a valuable source of continuous spatial and temporal data, facilitating the monitoring of vegetation dynamics across extensive regions (Hao et al., 2015).

One of the recent remote-sensing-based indices is the Normalized Difference Drought Index (NDDI). This index evaluates drought conditions by integrating data on soil moisture content and vegetation health, providing a comprehensive measure of an area's dryness or wetness. The NDDI is considered a superior tool for drought monitoring due to the following advantages:

Dual Monitoring Capability: By simultaneously assessing soil moisture and vegetation health, the NDDI captures two critical factors that influence drought severity, offering a more holistic evaluation.
Precipitation Sensitivity: The NDDI reflects the effects of precipitation more accurately than indices that focus exclusively on vegetation or soil metrics, making it more responsive to changes in water availability.

Reduced Environmental Noise: Unlike traditional indices such as the Normalized Difference Vegetation Index (NDVI) or the Normalized Difference Water Index (NDWI), the NDDI minimizes interference from atmospheric variations and seasonal vegetation changes, enhancing its reliability.

Satellite-Derived Simplicity: The NDDI relies entirely on satellite data, eliminating the need for supplementary ground-based meteorological measurements and simplifying its application across large and remote areas.

These advantages make the NDDI an excellent tool for accurately monitoring drought conditions and their impacts (Du et al., 2018; Xie et al., 2021). Trinh et al. (2019) examined the application of remote sensing techniques for drought assessment using the Normalized Difference Drought Index (NDDI) in Binh Thuan Province, Vietnam. They concluded that the results could be used to create drought-level maps and provide valuable information to help managers implement measures to minimize drought-related damage. Similarly, Rismayatika et al. (2020) applied the NDDI to identify dry areas on agricultural land in Magetan Regency, Indonesia, demonstrating its ability to detect drought with acceptable accuracy. Artikanur et al. (2022) utilized the NDDI to map drought intensity in the Bojonegoro region of Indonesia, identifying it as a suitable index for drought estimation and prediction. Salas-Martinez et al. (2023) estimated the NDDI using Landsat 8 multispectral images in the central zone of the Gulf of Mexico. They concluded that the NDDI effectively characterizes drought behavior during periods of reduced precipitation and increased temperatures. Patil et al. (2024) introduced the NDDI in a remote sensing-based study, combining NDVI and NDWI indices, and described it as an independent index that complements conventional drought estimation techniques. Affandy et al. (2024) employed the NDDI to assess agricultural drought in the Corong River basin, confirming its effectiveness in drought monitoring. Li et al. (2024) developed a novel composite drought index integrating precipitation, temperature, and evapotranspiration for drought monitoring in the Huang-Huai-Hai Plain. They used time-series analysis methods to analyze drought evolution, highlighting the index's utility in understanding drought patterns. Alshahrani et al. (2024) applied a Support Vector Machine-based Drought Index (SVM-DI) for regional drought analysis in northern Pakistan. They concluded that the SVM-DI methodology provides a unique approach to reducing the impact of extreme values and outliers when aggregating regional precipitation data.

This study leverages modern remote sensing methods and time-series analysis of the NDDI to enhance the understanding of drought patterns in the Khorramabad region, offering a robust tool for drought prediction and management. Conducting this research is essential, as its findings can contribute to scientific and executive decision-making in drought crisis management. The innovation of this research lies in its application of the NDDI for the first time in Iran, specifically within the Khorramabad watershed, to obtain and analyze drought conditions.

Materials and Methods

Study Area

The study area is the Khorramabad Watershed, located in Lorestan Province, Iran, and is a sub-basin of the Karkheh River basin. Covering an area of 161913 hectares, it includes the sub-basins adjacent to the city of Khorramabad and the Cham-Anjir River. Geographically, the watershed is situated between longitudes 48°03'36" to 48°46'12" E and latitudes 33°15'36" to 33°43'44" N, encompassing the Kamalvand and Central Khorramabad plains. The region is connected to neighboring counties via major roads, including the Borujerd-Khorramabad, Poldokhtar-Khorramabad, and Dorud-Khorramabad highways (Figure 1). The average annual precipitation and temperature recorded at the Khorramabad meteorological station are 466.44 mm and 16.98°C, respectively, with an average annual evaporation of 209 mm. The basin is located in the central part of the Zagros mountain range and features a complex geological structure (Amiri et al., 2023). Based on the De Martonne classification, the region's climate is categorized as semi-arid. Precipitation typically begins in October and continues until late May, while dry months experience minimal rainfall. The highest average monthly precipitation at the Khorramabad station is recorded in April (85.29 mm). The lowest and highest mean monthly temperatures occur in January (5.58°C) and August (29.92°C), respectively (Soleimani-Motlagh & Shakerami, 2021).

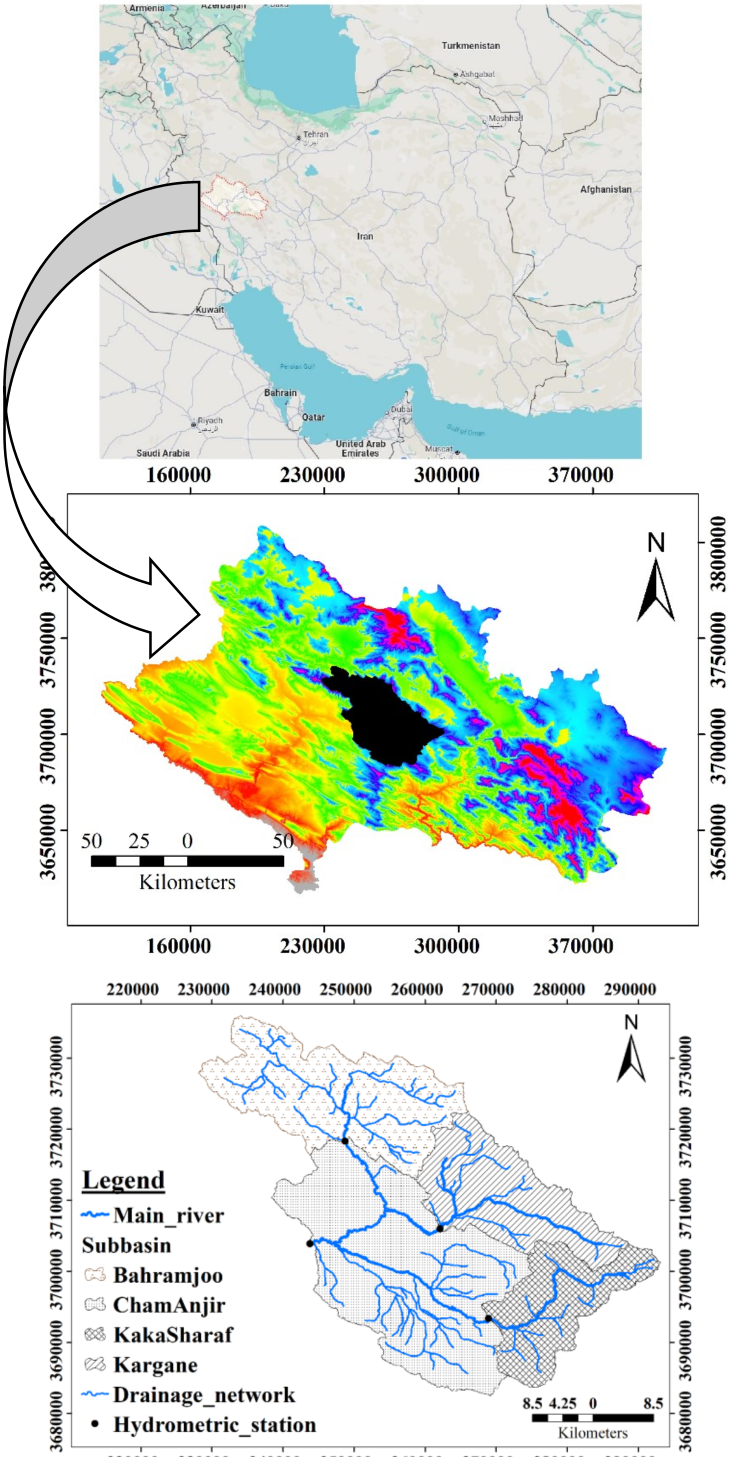

Figure 1. Location of the study area in Lorestan Province and Iran.

Methodology

The use of vegetation indices is one of the most practical approaches for drought monitoring using satellite data. These indices combine different spectral bands and leverage the contrast between spectral ranges to enhance the received spectral signal. This process improves the accuracy of identifying and analyzing different regions while minimizing interference across various wavelengths (Campos et al., 2012). These characteristics make indices such as the

Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Drought Index (NDDI) effective tools for studying environmental changes, analyzing vegetation cover, and assessing drought conditions. By utilizing these indices, spectral information is better interpreted, and environmental conditions can be modeled and analyzed with greater precision. To determine the NDDI drought index, Sentinel-2 satellite images from 2016 to 2023 were used on a seasonal time scale, totaling 32 images. Sentinel-2 imagery has been available since 2015, with a temporal resolution of five days. Sentinel-2A was launched on June 23, 2015, followed by Sentinel-2B on March 7, 2017. The Sentinel-2 satellites provide 12 spectral bands, categorized as follows:

1. Three 60-meter bands: B1, B9, and B10,
2. Four 10-meter bands: B2, B3, B4, and B8,
3. Five 20-meter bands: B5, B6, B7, B11, and B12.

The Google Earth Engine (GEE) system is an advanced and efficient tool for analyzing spatial and temporal data, offering rapid processing and large-scale data analysis capabilities across various environmental fields, including drought index estimation. This platform provides access to multiple up-to-date satellite datasets, enabling the extraction of indices such as the Standardized Precipitation Index (SPI), vegetation indices, evapotranspiration indices, and the Normalized Difference Drought Index (NDDI) with high accuracy and speed. GEE not only enhances the accuracy and efficiency of data analysis but also allows users to utilize real-time, high-quality datasets for evaluating drought conditions. In this study, the temporal and spatial variations of the NDDI drought index in the Khorramabad watershed were analyzed using GEE. The primary objective is to achieve a precise understanding of the spatiotemporal drought patterns in this region and provide a scientific basis for optimal water resource management. The complete workflow of the study is illustrated in Figure 2.

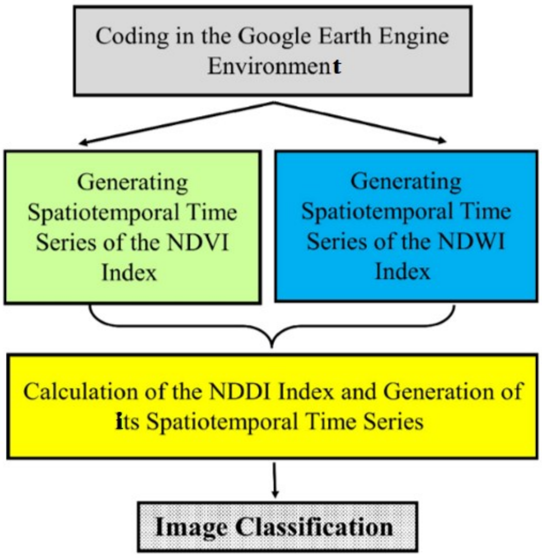

Figure 2. Flowchart of the remote sensing-based drought (NDDI) analysis (Patil et al. 2024)

NDDI Index

The Normalized Difference Drought Index (NDDI) is used for drought monitoring and is derived from a combination of the NDVI and NDWI indices (Patil et al., 2024). High NDDI values occur when both the vegetation index (NDVI) and water index (NDWI) decrease. Conversely, when NDDI values decrease, NDVI and NDWI values increase, indicating higher vegetation cover with sufficient moisture (Giovanni et al., 2018; Du et al., 2018). The NDDI is calculated using Equation (1):

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \quad (1)$$

where NDVI is the Normalized Difference Vegetation Index, NDWI is the Normalized Difference Water Index. The drought intensity based on NDDI values is classified into five categories: very low, low, moderate, high, and very high, as presented in Table 1.

Table 1. Drought severity by NDDI value (Nepal et al. 2021)

No.	NDDI Value	Drought Severity Class
1	<-2	Very Low
2	-02 - 0.7	Low
3	0.7 - 1.25	Moderate
4	1.25 - 3	High
5	>3	Very high

NDVI Index

The Normalized Difference Vegetation Index (NDVI), calculated from remote sensing images, is a widely used index for drought monitoring. It is computed using Equation 2 with Sentinel-2 data. This index distinguishes vegetation cover from the background soil and provides valuable insights into vegetation health (Zhang et al., 2020; Kamble et al., 2010; Affandy et al., 2024). NDVI is based on the difference in reflectance intensity between the red and near-infrared bands. Positive values indicate healthy vegetation, while values close to zero or negative reflect low or no vegetation (Rouse et al., 1973).

However, it is important to note that the NDVI index alone is not sufficient for identifying drought. Precipitation and soil moisture data from microwave satellite sensors are also essential for drought monitoring. Studies have shown that NDVI exhibits a slow response to precipitation deficits (Sahoo et al., 2015; Liu et al., 2017), whereas the NDWI (Normalized Difference Water Index), which uses both bands in the near-infrared region, is more sensitive to rainfall (Guha, 2019).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

where NIR represents the Near-Infrared band and RED represents the Red band.

NDWI Index

The Normalized Difference Water Index (NDWI), also referred to as the Water Index, was first proposed by McFeeters in 1996 for identifying surface water in wetlands and measuring the extent of surface water. It is calculated for the Sentinel-2 sensor using Equation 3:

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{3}$$

where NIR represents the near-infrared band, and Green represents the green band. Accordingly, water bodies have positive values, while vegetation and soil have values close to zero or negative for this index (Faizollahpour, 1402). This index is based on the fact that liquid water bodies typically reflect more light in the blue spectrum compared to the green and red spectra. Clear water appears blue due to reflection in the visible blue spectrum, while turbid water, due to low reflection in the near-infrared (NIR) band, reflects more in the visible spectrum (Affandy et al., 2024). The range of NDWI values is from -1 to +1. If the NDWI value is above zero, it indicates an area with surface water; if the value is below zero, it indicates an area without water (Rismayatika et al., 2020). In other words, a positive NDWI indicates no drought in the region since the area contains water.

Forecasting Using Time Series Models

Time series modeling is an effective and widely used method for forecasting climatic variables. In this study, statistical models such as AR (Equation 4), MA (Equation 5), ARMA (Equation 6), ARIMA, and SARIMA are employed for drought forecasting. All these models were implemented in the R software environment for simplification and more accurate analysis.

$$Z_t = \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \cdots + \varphi_p Z_{t-p} + \alpha_t \tag{4}$$

$$Z_t = \alpha_t - \theta_1 \alpha_{t-1} - \theta_2 \alpha_{t-2} - \cdots - \theta_q \alpha_{t-q} \tag{5}$$

$$Z_t = \varphi_1 Z_{t-1} + \cdots + \varphi_p Z_{p-t} + \alpha_t - \theta_1 \alpha_{t-1} - \cdots - \theta_q \alpha_{t-q} \qquad (6)$$

In the above equations, φ_1, φ_2, and φ_p are the coefficients and parameters of the AR model, and θ_1, θ_2, and θ_q are the coefficients and parameters of the MA model. α_t represents the independent random variable (Box et al., 2016). In this study, the NDDI index time series for the years 2016 to 2023 was used for forecasting. The data were split into two sections: the training period (first four years) and the validation period (next four years). During the validation phase, the model's performance was evaluated and compared with actual data to test its accuracy and efficiency. After training and validation, drought forecasts for the next three years were made.

During the data preparation step, the error components, including trend, seasonal changes, and the random component, were removed. Then, the random component was modeled using time series. In the model identification phase, the most appropriate models fitted to the data were selected. In the model evaluation phase, the chosen model was assessed using statistical criteria such as the Akaike Information Criterion (AIC) (Equation 7) and R-squared (R^2) (Equation 8). The best model for forecasting is the one with the lowest AIC and highest R^2 (Akaike, 1974).

$$AIC(K) = n\ln(MSE) + 2k \qquad (7)$$

$$R^2 = \frac{[\sum_{i=1}^{n}(x_{oi} - \bar{x}_o)(x_{si} - \bar{x}_s)]^2}{\sum_{i=1}^{n}(x_{oi} - \bar{x}_o)^2 (x_{si} - \bar{x}_s)^2} \qquad (8)$$

where n is the number of time series data points, k is the number of estimated parameters in the models, MSE is the mean squared error, x_{si} is the estimated values of the variable, x_{oi} is the observed values, $\bar{x}_o$ is the mean of the observed data and $\bar{x}_s$ is the mean of the estimated data. The R-squared value ranges from 0 to 1, where values closer to 1 indicate a better fit of the model, and a value of 1 indicates a perfect simulation.

Discussion and Results

NDVI Index

The NDVI index, the most prominent vegetation index, was first introduced by Tucker and Choudhury in 1987 for drought monitoring. It reflects the relationship between spectral diversity and changes in vegetation cover at different growth rates (Affandy et al., 2024). This index is widely used for assessing vegetation cover at both regional and global scales and is closely linked to plant structure and photosynthetic activity (Xue & Su, 2017). The spatial and temporal patterns of the NDVI index within the Khorramabad watershed are illustrated in Figures 3 and 4. As shown in Figure 3, NDVI values exhibited a declining trend from 2016 to 2023. The lowest NDVI values were consistently observed in the western parts of the watershed during the winter months, while the highest values were recorded in the central region during winter and along the basin's edges during other seasons. Figure 4 highlights the temporal variations in NDVI, which ranged from 0.08 in autumn 2022 to 0.23 in spring 2019. It is important to note that a total of 32 NDVI images were analyzed for the study period. However, due to page limitations, only the images from the first year (2016) and the last year (2023) are presented in this study.

These findings provide valuable insights into the dynamics of vegetation cover in the Khorramabad watershed and underscore the utility of the NDVI index in monitoring environmental changes over time. The observed trends can serve as a basis for further research and inform strategies for sustainable land and resource management in the region.

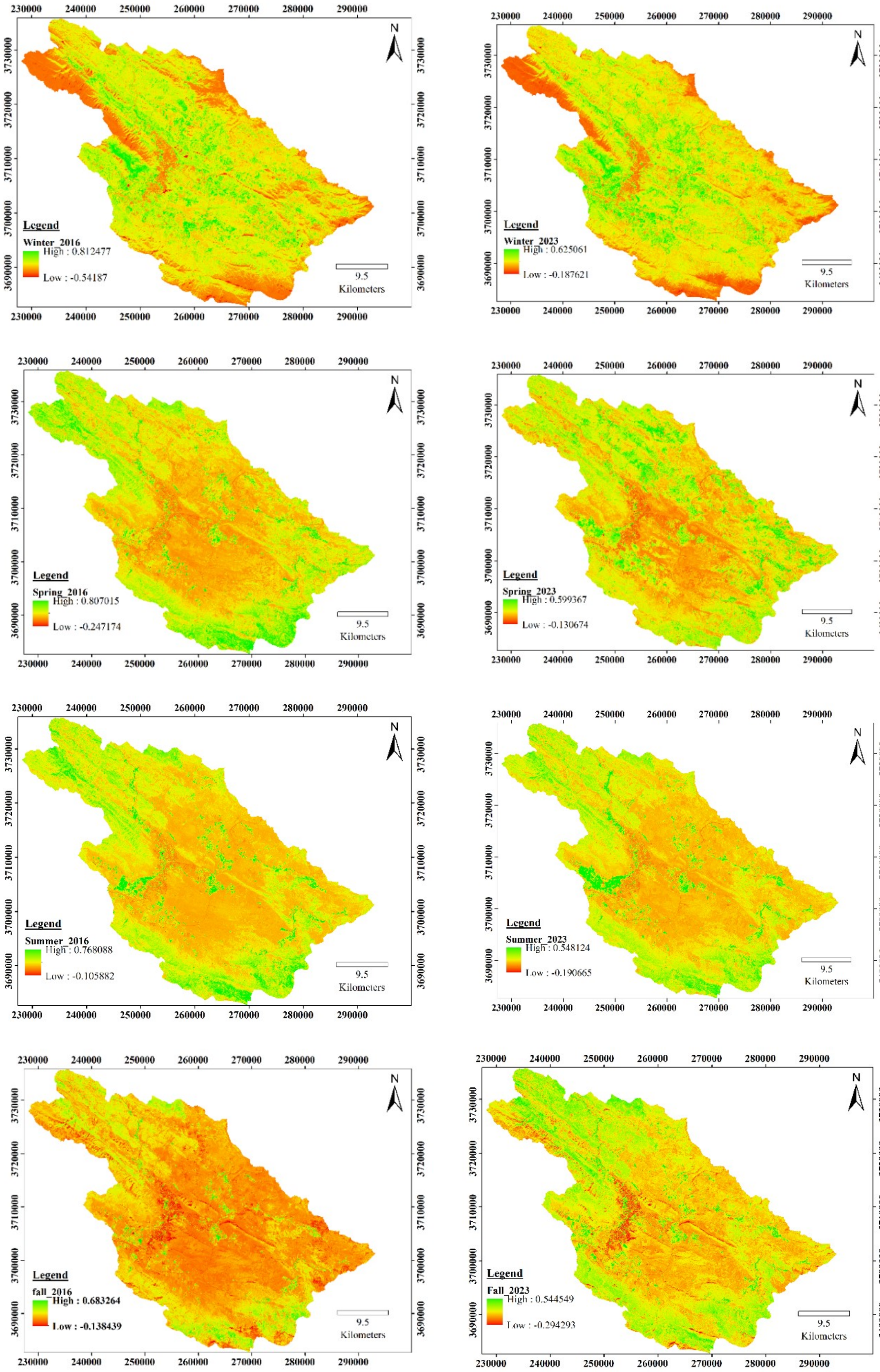

Figure 3. Map of spatial changes in the NDVI index in the Khorramabad watershed in the years 2016 and 2023.

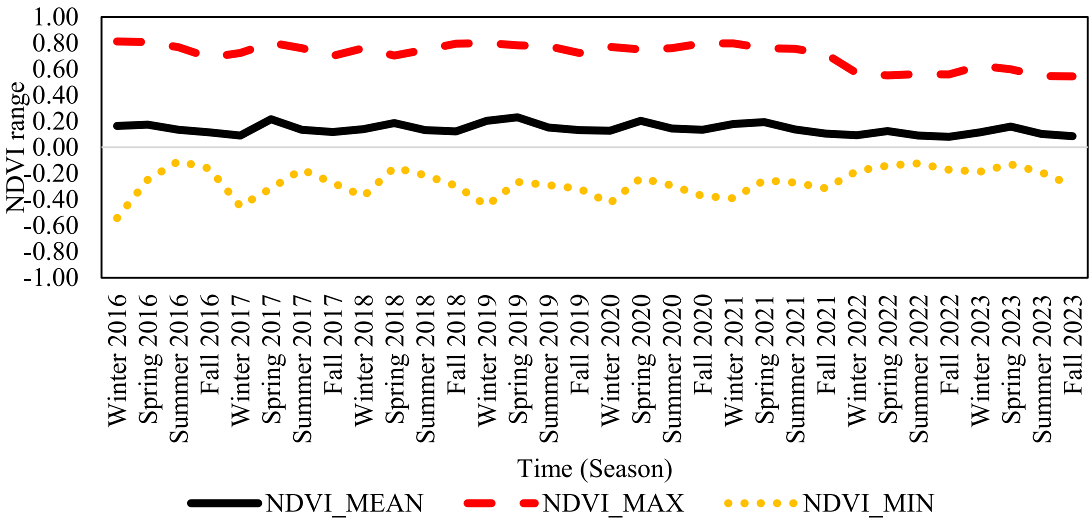

Figure 4. Temporal changes in the NDVI index in the Khorramabad watershed from 2016 to 2023.

NDWI Index

An increase in the NDWI over time can signify an improvement in water resources, increased rainfall, or enhanced water conditions, while a decrease may reflect drought, climate change, or the degradation of water resources. The spatial and temporal patterns of NDWI changes in the Khorramabad watershed are illustrated in Figures 5 and 6, respectively. According to Figure 5, between 2016 and 2023, the highest NDWI values were observed in the western parts of the watershed during the winter months, while in other seasons, they were concentrated in the central region of the basin. Conversely, the lowest NDWI values were recorded in the central area during winter and along the basin's edges during other seasons. Figure 6 demonstrates that the temporal changes in the NDWI index ranged from 0.08 in autumn 2022 to 0.23 in spring 2019.

Figure 7 explores the relationship between the NDVI (Normalized Difference Vegetation Index) and NDWI indices, revealing a strong negative correlation between them (R^2 = 0.76). The results indicate that the highest NDWI values were associated with areas of poor vegetation cover, while the lowest NDWI values were found in areas with dense vegetation cover (Gerardo et al., 2022). In other words, when NDVI values are low, NDWI tends to increase, suggesting higher drought intensity in the region due to the lack of vegetation. On the other hand, when NDVI values are high, NDWI gradually decreases, as vegetation helps retain water in the area, creating a favorable environment for water and soil conservation (Huang et al., 2022).

It is important to note that a total of 32 NDWI images were analyzed over the study period. However, due to page limitations, only the images from the first year (2016) and the last year of the study period (2023) are presented. These findings highlight the dynamic interplay between vegetation and water resources in the Khorramabad watershed and provide valuable insights for understanding drought patterns, water resource management, and environmental conservation in the region.

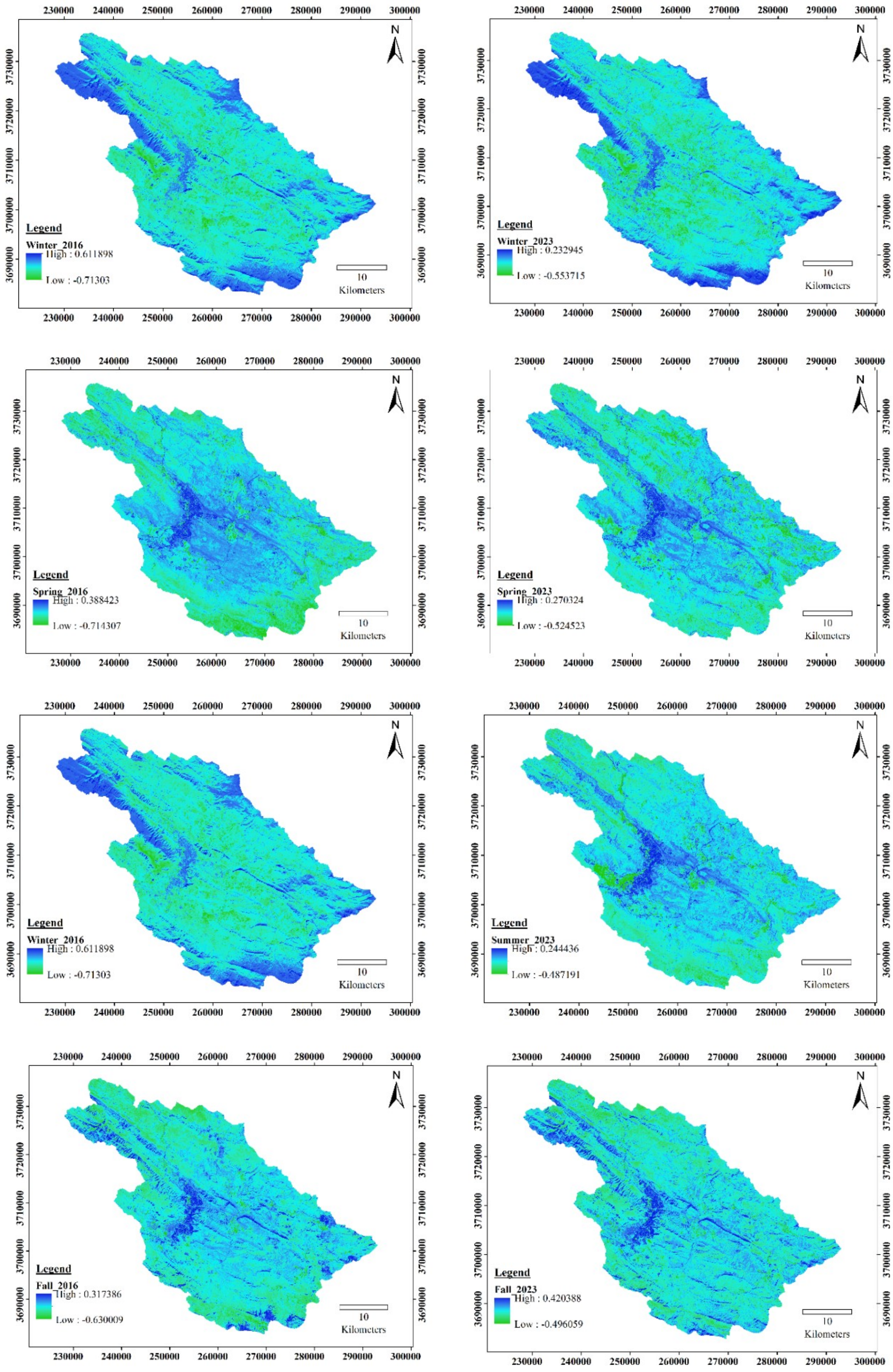

Figure 5. Map of spatial changes in the NDWI index in the Khorramabad watershed in the years 2016 and 2023.

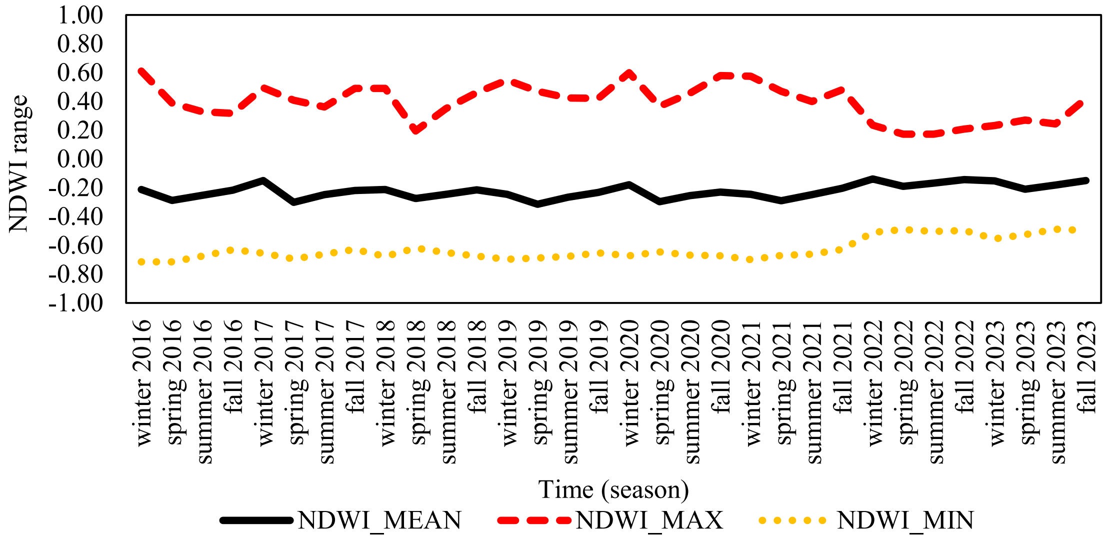

Figure 6. Temporal changes in the NDWI index in the Khorramabad watershed from 2016 to 2023.

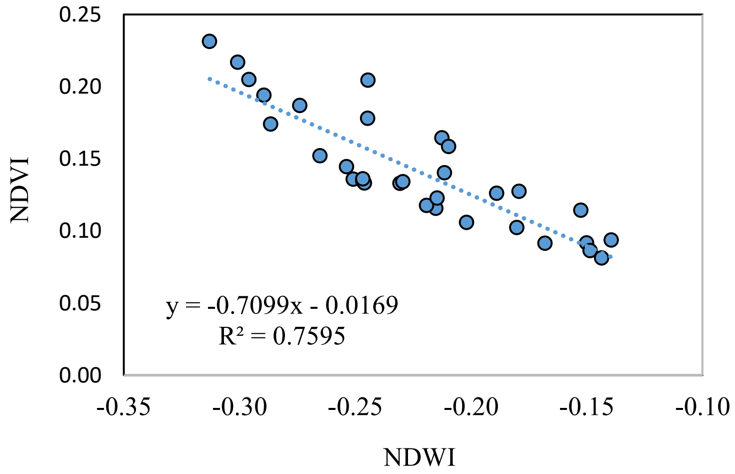

Figure 7. The relationship between the NDVI and NDWI indices.

NDDI Index

The NDDI is derived from a combination of NDVI and NDWI data. NDVI utilizes radiation absorption to measure chlorophyll content and mesophyll structure in vegetation canopies, while NDWI assesses canopy moisture based on water content and mesophyll properties. In the NDDI index, lower values indicate areas with denser and wetter vegetation cover, whereas higher values correspond to drier regions (Affandy et al., 2024). Figure 8 illustrates the spatial distribution of this drought index across the Khorramabad watershed. According to this figure and the classification provided in Table 1, the majority of the study area over the 8-year period falls within the "very low drought severity" class (Row 1 in the table). As shown in Figure 9, the temporal changes in the NDDI index range between -3.20 and -11.21, and throughout the study period, the area consistently remains in the "very low drought severity" class. Figure 8 also highlights that in the winter of 2019, the highest NDVI value (0.2) and the lowest NDWI value (-0.24) were recorded. This inverse relationship between NDVI and NDWI further underscores the strong negative correlation observed earlier, where areas with higher vegetation density (high NDVI) tend to retain more moisture (lower NDWI), while areas with sparse vegetation (low NDVI) exhibit higher drought intensity (higher NDWI). These findings emphasize the utility of the NDDI index in monitoring drought conditions and understanding the interplay between vegetation health and water availability in the Khorramabad watershed. The consistent classification of the region within the "very low drought severity" class suggests relatively stable environmental conditions during the study period, though localized variations in NDVI and NDWI highlight the importance of continuous monitoring to address potential future challenges related to climate change and water resource management.

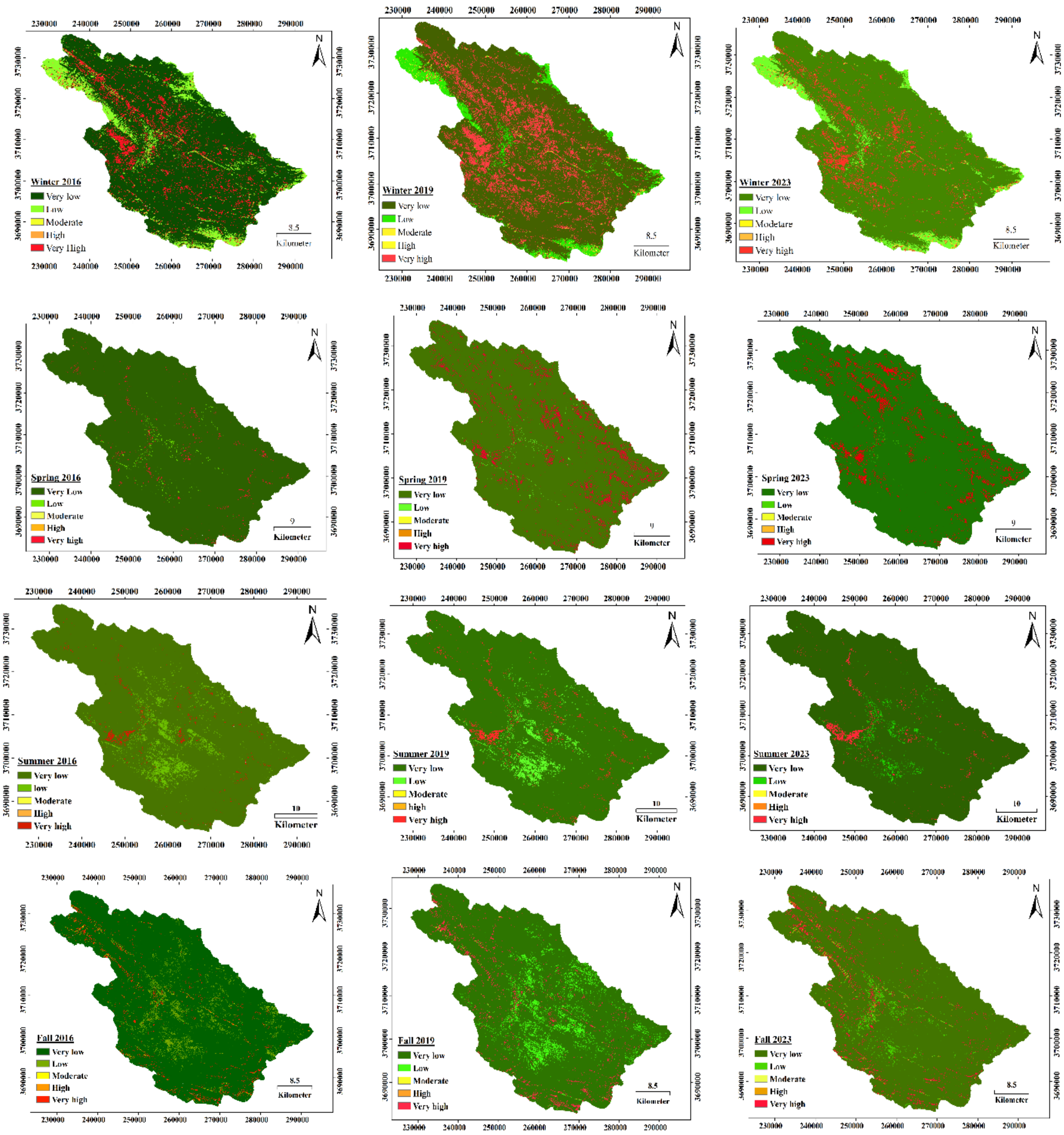

Figure 8. Map of spatial changes in the NDDI index in the Khorramabad watershed in the years 2016 and 2023.

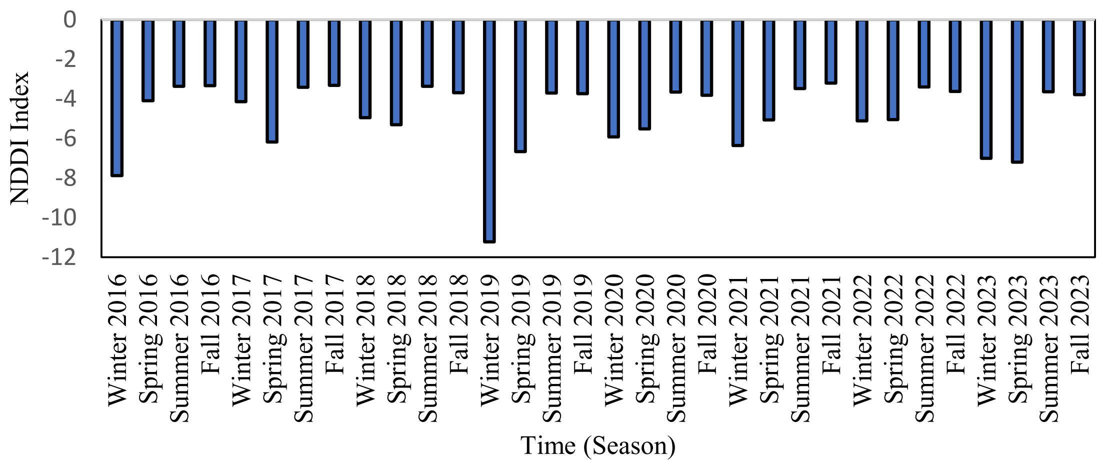

Figure 9. Temporal changes in the NDDI index in the Khorramabad watershed from 2016 to 2023.

Prediction of NDDI Index Using Time Series Models

To predict the NDDI index, the Forecast package in R software was used. As mentioned in the Materials and Methods section, the data from 2016 to 2023 were first decomposed into random, trend, and seasonal components using the instructions embedded in the Forecast package (Figure 10). Then, by training on 50% of the first portion of the data, the models were defined, and their coefficients and Akaike criteria were extracted (Table 2). Next, based on the random component of the selected models, the prediction for the second 50% of the data was performed, and the accuracy and fit were evaluated through the graph in Figure 11 and Table 2.

According to Figure 11, the models AR1, AR2, MA1, MA2, ARMA(1,1), ARMA(2,2), ARMA(1,2), ARMA(2,1), ARIMA(1,1,2), and ARIMA(2,1,1) showed a good fit for the NDDI series. Although the results of other models, such as SARIMA(1,1,2)(0,1,2)(1,2) and SARIMA(1,1,1)(0,1,1)(1,2), also show a relatively good fit with the series, they exhibited underestimation or overestimation during extreme data events. Additionally, the results from the model characteristics table, such as coefficients and Akaike criteria, indicate that the Akaike values for the models MA1, MA2, ARMA (1,1), and ARMA (1,2) are below 50, while other models are above 50. For the SARIMA model series, the Akaike values range from approximately 21 to 26. Regarding the coefficients, the absolute values of the coefficients for the models AR1, AR2, MA2, and the SARIMA series models are less than 1.

Soleimani-Motlagh et al. (2017) and Mirazavand et al. (2015) showed that a suitable model should have a low Akaike criterion and absolute coefficients below 1. Based on this principle and the evaluation of the coefficients' correlation with the NDDI series, the AR1, AR2, and MA2 models (which have the highest coefficient of determination (about 92%) and coefficients below 1 with low Akaike values) are the most suitable models. Finally, after further evaluation of model selection criteria, the MA2 model was chosen due to its Akaike criterion being lower than 50 compared to AR1 and AR2 models. This model was used for predicting the NDDI series for the years 2024 to 2026.

The prediction was made based on the random component of the NDDI data series, assuming that the trend and seasonal components would follow the pattern of the last three years. As shown in Figure 12, in winter and spring of 2024, the NDDI index decreased, indicating better rainfall and water reserves, while this trend increased in summer and autumn of 2024, reflecting a shortage of rainfall, water reserves, and reduced vegetation cover. This trend is expected to continue the following year, with improved water resource conditions expected in the spring and winter of 2025 and 2026.

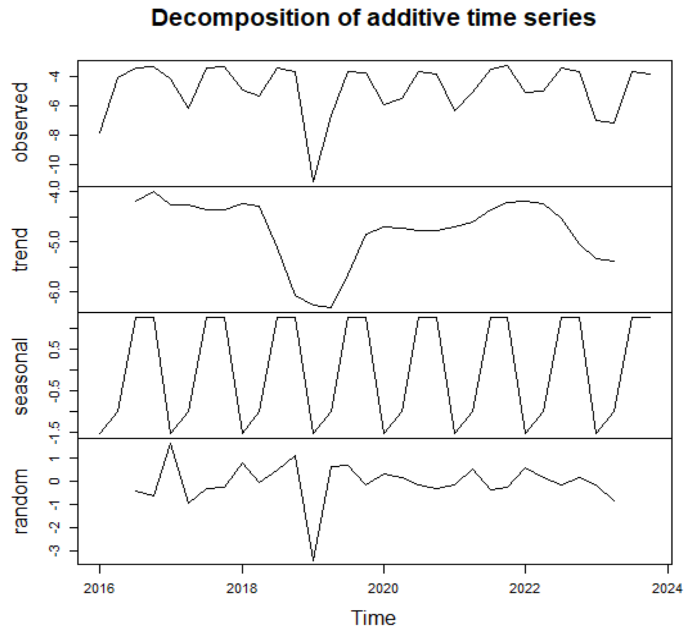

Figure 10. Decomposition of the NDDI time series into random, trend, and seasonal components.

Table 2. Results of time series models for the NDDI index in the Khorramabad watershed.

No.	Time Series	Coeff.		AIC	R^2	RMSE
1	AR(1)	AR1	-0.3363	52.42	0.92	0.39
2	AR(2)	AR1	-0.4616	52.51	0.92	0.40
		AR2	-0.3259			
3	MA(1)	MA1	-1	47.19	0.92	0.38
4	MA(2)	MA1	-0.8586	47.97	0.92	0.38
		MA2	-0.1414			
5	ARMA(1,1)	AR1	0.0969	49.05	0.92	0.38
		MA1	-1			
6	ARMA(1,2)	AR1	-0.7190	49.65	0.92	0.38
		MA1	0			
		MA2	-1			
7	ARMA(2,1)	AR1	0.08	50.47	0.92	0.38
		AR2	-0.19			
		MA1	-1			
8	ARMA(2,2)	AR1	-0.7582	51.59	0.91	0.41
		AR2	-0.0663			
		MA1	0			
		MA2	-1			
9	ARIMA(1,1,2)	AR1	0.2180	53.22	0.92	0.37
		d	1			
		MA1	-1.9699			
		MA2	1			
10	ARIMA(2,1,1)	AR1	-0.4161	54.52	0.92	0.40
		AR2	-0.2828			
		d	1			
		MA1	-1			
11	SARIMA(1,1,2)(0,1,2)(1,2)	AR1	-0.0589	25.82	0.42	1.42
		MA1	-0.0607			
		MA2	-0.2506			
		SMA1	0			
		SMA2	0			
12	SARIMA(1,1,1)(0,1,1)(1,2)	AR1	0.6235	21.84	0.31	5.83
		MA1	-0.9998			
		SMA1	0.7784			

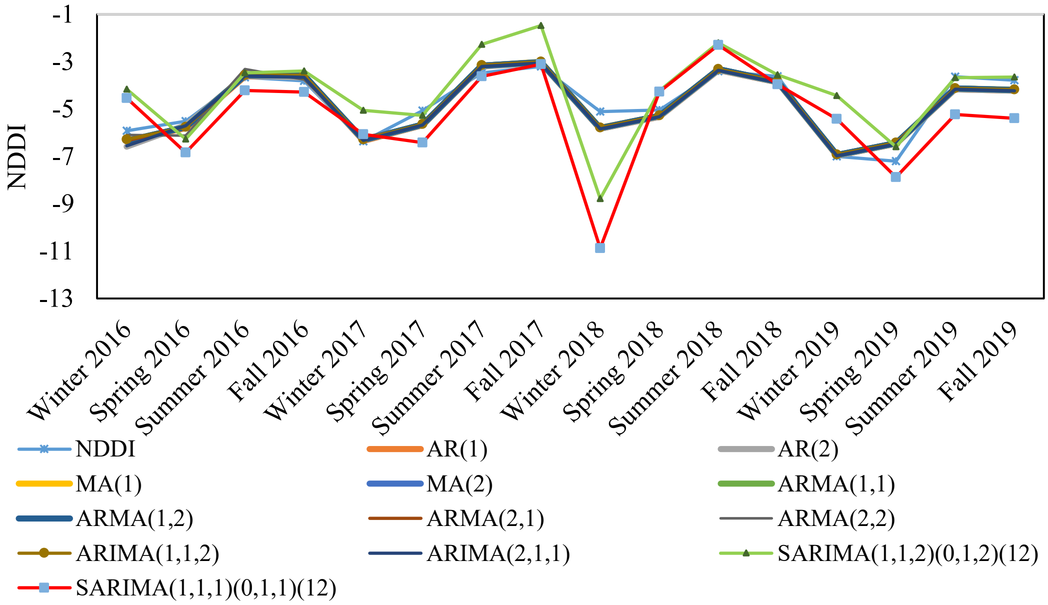

Figure 11. Fit of time series models to the NDDI series.

The best model identified was MA2 (Moving Average of order 2). The next step involved making predictions for the next seasons, spanning from Winter 2020 to Autumn 2023, as detailed in Table 3. To evaluate the accuracy of the forecasts, the Mean Squared Error (MSE) method was employed. A low MSE value, or one close to zero, indicates that the forecasted results closely align with the actual data, making the model suitable for future forecasting. In this study, the obtained MSE value was 0.15, demonstrating the model's reliability for predictive calculations.

Table 3. Results of NDDI using MA2

Number	Period	Actual	Forecast	Number	Period	Actual	Forecast
1	Winter 2020	-5.92	-6.35	9	Winter 2022	-5.11	-5.80
2	Spring 2020	-5.51	-5.77	10	Spring 2022	-5.03	-5.29
3	Summer 2020	-3.65	-3.57	11	Summer 2022	-3.40	-3.32
4	Autumn 2020	-3.81	-3.58	12	Autumn 2022	-3.62	-3.84
5	Winter 2021	-6.36	-6.30	13	Winter 2023	-7.00	-6.93
6	Spring 2021	-5.06	-5.65	14	Spring 2023	-7.20	-6.43
7	Summer 2021	-3.47	-3.16	15	Summer 2023	-3.63	-4.13
8	Autumn 2021	-3.21	-3.01	16	Autumn 2023	-3.78	-4.19

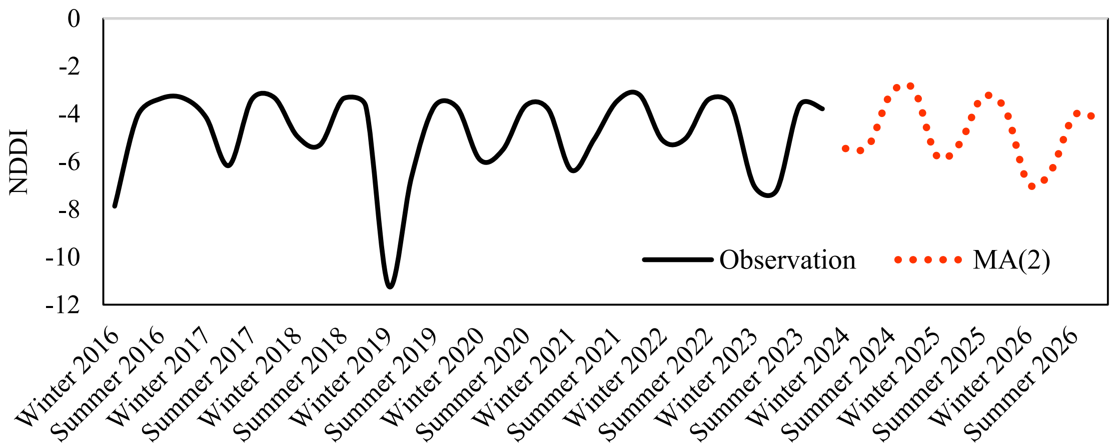

Figure 12. Prediction of the NDDI series based on the MA2 model.

Conclusion

In this study, we examined the drought status in the Khorramabad watershed from 2016 to 2023 using the Normalized Difference Drought Index (NDDI) to assess vegetation cover and water bodies. The results revealed that higher vegetation density, as indicated by higher NDVI values, corresponds to lower NDDI values, reflecting reduced drought severity. This finding aligns with the results of Artikanur et al. (2022). Furthermore, the analysis of the relationship between NDVI and NDWI demonstrated a strong negative correlation, consistent with the findings of Gerardo et al. (2022). When NDVI values are low, NDWI values tend to increase, indicating higher drought intensity due to reduced vegetation. Conversely, as NDVI increases, NDWI values gradually decrease. This relationship underscores the critical role of vegetation in water storage and drought mitigation, as vegetation helps maintain soil moisture and regulate the water cycle, in line with the results of Huang et al. (2022). By evaluating various time series models for predicting NDDI-based drought conditions, the MA2 model was identified as the best predictive model, supported by an Akaike Information Criterion (AIC) value of less than 50. The results indicate that the decrease in the NDDI index during spring and winter 2024 reflects improved rainfall and water reserves. Additionally, predictions suggest a declining trend in the index for spring and winter 2025 and 2026, attributed to increased rainfall, enhanced water storage, and expanded vegetation cover. Conversely, the increasing trend in the index during summer and autumn of 2025 and 2026 is linked to reduced rainfall, declining water reserves, and deteriorating vegetation cover. The predictions also highlight an improvement in water resources during winter 2026, with conditions expected to be better than in previous periods. These findings emphasize the importance of analyzing seasonal trends and cyclical patterns for effective water resource management and agricultural planning. Overall, this study demonstrates the effectiveness and reliability of NDVI, NDWI, and NDDI as robust indices for monitoring vegetation dynamics and drought stress conditions.

Conflict of Interest

The authors declare that they have no conflict of interest.

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